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Estimating Production Risk and Inefficiency Simultaneously: An Application to Cotton Cropping Systems

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By using a stochastic frontier framework, the mutual effect of input use on production risk and inefficiency is investigated. Disentangling this mutual effect proves important for empirical reasons, at least when applied to west Tennessee cotton systems grown after various cover crops. The most striking result is that the stochastic frontier model, when compared with a typical Just-Pope model, reorders the relative riskiness of cover-crop regimes associated with the cotton systems.

Key words: cotton, inefficiency, Just-Pope, production risk, stochastic production frontier

Introduction

The specification of residuals from a production model's deterministic portion plays a central role in two generally separate analytic frameworks, each dating from the late 1970s. Risk analysis in a Just-Pope (1978, 1979) framework involves recovering the residuals and using them to investigate the marginal effects of inputs on production risk, or noise. One of the specification requirements of the Just-Pope framework is that there be no a priori restrictions on the marginal risk effects so that an input to production could be either risk-increasing or risk-decreasing. Recent empirical applications include Asche and Tveterås; Smale et al.; Traxler et al.; and Tveterås, among others.

In contrast, inefficiency analysis in a stochastic frontier framework (Aigner, Lovell, and Schmidt; Battese and Corra; Meeusen and van den Broeck) involves specifying the residuals with both a two-sided white noise component and a one-sided inefficiency component. Recent empirical applications (including Morrison-Paul, Johnston, and Frengley; Goaied and Ayed-Mouelhi; Cuesta; Reinhard, Lovell, and Thijssen; Battese and Broca; and Ahmad and Bravo-Ureta), which generally focus only on the inefficiency component, estimate either technical inefficiency or the marginal effects of inputs or exogenous factors on inefficiency.

Recently, however, researchers have noted that the stochastic frontier model is compatible with the Just-Pope model and have begun combining risk and inefficiency analysis

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in a single framework (Wang; Kumbhakar 1993, 2002; Kumbhakar and Lovell; Battese, Rambaldi, and Wan). Use of a combined framework, which simultaneously accounts for inefficiency and marginal impacts on production risk, may affect empirical results based on a Just-Pope model, which addresses only risk. For instance, using a Just-Pope framework, Tveterås found labor to be risk-reducing but capital to be risk-increasing in Norwegian salmon farming. However, while investigating a similar application but using a stochastic frontier framework, Kumbhakar (2002) found partially conflicting results: both capital and labor were risk-reducing.[1] This partial reversal of Tveterås' results therefore points toward a likely mutuality between risk and inefficiency effects associated with input use that is revealed only through Kumbhakar's systematic accounting of two components of the residuals—noise and inefficiency.

In a similar fashion, the present study investigates potential discrepancies in risk analysis results obtained using the typical Just-Pope and stochastic frontier frameworks. By conducting a risk analysis within a stochastic frontier framework, one can investigate whether inputs remain risk-increasing (or -decreasing) even after accounting for inefficiency. This analytic framework is applied to experimental cotton production systems grown with various cover crops and alternative tillage systems in west Tennessee. Two empirical questions are of particular interest: first, whether or not a production system of cotton grown with a cover crop is riskier than cotton grown without one, and second, whether the choice of analytic framework (Just-Pope or stochastic frontier) affects the answer to the first question. Using cotton production systems as an example, this analysis seeks to determine whether the use of a stochastic frontier framework will duplicate or reverse the results reported by Larson et al., who used a Just-Pope framework to show that a hairy vetch cover crop increased the cotton system's riskiness.

The Production Framework

A production function commonly associated with the stochastic frontier framework is given by

$$\ln(y_i) = f(\mathbf{x}_i, \beta) + v_i - u_i, \tag{1}$$

where y_i is a scalar output of production unit i $\{i = 1, ..., I\}$, $\mathbf{x}_i$ is a vector of N inputs used by producer i, $f(\mathbf{x}_i, \beta)$ is the deterministic part of the production frontier, β is a vector of technology parameters to be estimated, and v_i and u_i are noise and inefficiency components which can take a number of forms, depending on specific assumptions. The form given by (1) is consistent with the typical Just-Pope framework under the following assumptions:[2]

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[1] Moreover, Kumbkahar (2002) found that both capital and labor were inefficiency-reducing. Both the Kumbkahar and Tveterås studies investigate risk effects in the production of the same commodity—Norwegian salmon—using similar data. More generally, however, there is no theoretical basis for comparing individual risk effects across production of different commodities.

[2] As pointed out by a reviewer, the normality assumption is not required in a Just-Pope framework, and Just and Pope (1978) proposed a general form that included a one-sided error term. The normality assumption is used here to promote parallel construction with the stochastic frontier models that follow. A Just-Pope model is often specified as follows:

$$y_i = f(\mathbf{x}_i, \beta) + h(z_i; \gamma)v_i, \; E(v_i) = 0, \; E(v_i^2) = 1, \text{ and } E(v_i, v_k) = 0, \text{ for } i \neq k.$$

Also, the model in (1) and (2) is not technically a Just-Pope model because output is written in log form, and hence not all of Just and Pope's (1978) properties hold. In the application, the use of the log of output facilitates estimation; however, including the natural log of inputs is impossible in the application because some input values (i.e., for applied nitrogen) equal zero.

$$(2)\qquad \begin{aligned} u_i &= 0, \\ v_i &\sim N(0, \sigma_{vi}^2), \\ \sigma_{vi}^2 &= \exp(\mathbf{z}_i^{v\prime}\delta^v), \end{aligned}$$

where $\mathbf{z}_i^v$ is an input vector which may or may not equal $\mathbf{x}_i$, and δ^v is a vector of parameters. The linear form of the variance equation is so specified with later estimation in mind. The basic stochastic frontier framework also starts with (1) but relies on the following assumptions:

$$(3)\qquad \begin{aligned} v_i &\sim N(0, \sigma_v^2), \\ u_i &\sim N^+(0, \sigma_u^2), \end{aligned}$$

where $N^+(0, \sigma_u^2)$ is the half-normal distribution, though other one-sided distributions are valid. A stochastic frontier model more comparable to the Just-Pope model allows for heteroskedasticity in the noise component:

$$(4)\qquad \begin{aligned} v_i &\sim N(0, \sigma_{vi}^2), \\ \sigma_{vi}^2 &= \exp(\mathbf{z}_i^{v\prime}\delta^v), \\ u_i &\sim N^+(0, \sigma_u^2). \end{aligned}$$

A stochastic frontier model that not only allows for heteroskedasticity in the noise component to investigate risk effects but also allows for heterogeneity in the mean of the inefficiency term to investigate inefficiency effects is given by (1), with the following assumptions:

$$(5)\qquad \begin{aligned} v_i &\sim N(0, \sigma_{vi}^2), \\ \sigma_{vi}^2 &= \exp(\mathbf{z}_i^{v\prime}\delta^v), \\ u_i &\sim N^+(\mu_i, \sigma_u^2), \\ \mu_i &= \mathbf{z}_i^{u\prime}\delta^u, \end{aligned}$$

where $\mathbf{z}_i^u$ is an input vector which may or may not equal $\mathbf{x}_i$ or $\mathbf{z}_i^v$, and δ^u is a vector of parameters.

The representation in (1) and (5) is virtually identical to Wang's model number (iii). It is also similar to that used by Kumbhakar (2002), except (5) allows for heteroskedasticity in the v_i and heterogeneity in the μ_i instead of heteroskedasticity in both the v_i and u_i. One can see that the specification given by (2) is a special case of (4), which in turn is a special case of (5). Moreover, the specification given by (3) is also a special case of (4), and therefore (5).

Estimation of the typical Just-Pope model given by equations (1) and (2) can be accomplished by maximum likelihood or generalized least squares in a two-step procedure. Marginal risk effects are given by $\hat{\delta}^v$, which may be positive or negative. Estimation of the stochastic frontier model given by equations (1) plus (3), (4), or (5) is more difficult because of the two error components. Nonetheless, the likelihood function associated with (1) and (5) can be specified, and therefore maximum-likelihood estimation is possible with a program such as Matlab.

For the simpler case given by (1) and (3), Kumbhakar and Lovell show the log-likelihood function is specified as

$$\ln L = \text{constant} - I\ln(\sigma) + \sum_i \ln\left(\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right)\right) - \frac{1}{2\sigma^2}\sum_i \varepsilon_i^2, \tag{6}$$

where $\varepsilon_i = v_i - u_i$, $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, and $\Phi(\cdot)$ is the standard normal cumulative distribution function. Kumbhakar and Lovell (p. 75) note that λ, a recoverable parameter, "provides an indication of the relative contributions of u and v to ε." Maximum-likelihood estimation based on (6) will generate estimates of $\varepsilon_i = v_i - u_i$, but firm-level inefficiency analysis requires the conditional distribution of u_i given ε_i and the estimator $E[u \mid \varepsilon]$, as derived by Jondrow et al.

If the inefficiency component is modeled as in (5), Kumbhakar and Lovell provide a more generalized likelihood function:

$$\ln L = \text{constant} - \sum_i \left[\ln(\sigma_i) + \ln\left(\Phi\left(\frac{\mu_i}{\sigma_u}\right)\right) - \ln\left(\Phi\left(\frac{\mu_i}{\sigma\lambda} - \frac{e_i\lambda}{\sigma}\right)\right) + \frac{1}{2}\left(\frac{e_i + \mu_i}{\sigma}\right)^2\right], \tag{7}$$

where $e_i = \ln(y_i) - f(\mathbf{x}_i, \beta) = v_i - u_i$. The following application is among the first to simultaneously estimate marginal inefficiency effects and marginal risk effects, now given by $\hat{\delta}^v$.

Application to Experimental Cotton Production Data

Planted after a cash crop, cover crops such as winter wheat, hairy vetch, or crimson clover are often used to improve soil and water resources and, potentially, the productivity or profitability of the cash crop. Despite these goals, adoption has been relatively uncommon. For example, Padgitt et al. report that only 0.9 million U.S. cotton acres (7% of total) were planted with cover crops over the period 1990–97.[3] The production relationships between a cover and cash crop are difficult to quantify. Legume cover crops such as vetch and clover can add nitrogen, while winter wheat and other non-legumes can decrease nitrogen availability. Moreover, the use of covers can break certain pest cycles, but it can also add to pest pressures by helping to create a favorable habitat for pests. With these uncertainties, it is perhaps not surprising that the adoption of cover crop systems is not widespread.

One potential economic barrier to cover crop adoption is the extra cost of establishing the cover. Another is the potential for cover crops to increase the variability of yield in the cash crop. Among the few attempts to investigate the riskiness of cotton-cover systems, Giesler, Paxton, and Millhollon found that a hairy vetch winter cover followed by cotton with no applied nitrogen fertilizer was "risk efficient" for a wide range of absolute risk aversion. Additionally, Larson et al. reported that winter wheat or clover covers, under some nitrogen rates and tillage regimes, could reduce yield variability. In contrast, however, Larson et al. also found that a vetch cover increased yield variability.

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[3] Regional differences can affect adoption rates. For example, 38% of Tennessee cotton acres but only 4% of Arizona cotton acres were grown with a cover crop (Padgitt et al.).

The production models given by (1) plus (2), (3), (4), or (5) are applied here to agricultural data generated by an agronomic experiment designed to investigate the effectiveness of alternate cover crops and tillage methods in cotton production from 1984 to 1997 at the West Tennessee Experiment Station, Jackson, TN.[4] The experiment used to generate the data for the present application (the same used by Larson et al.) was a randomized complete block with split plots and four replications per year. Nitrogen fertilizer was varied in the main plots and winter cover and tillage methods were varied in the split plots. The same plots received the same nitrogen fertilizer rate, cover crop, and tillage treatment each year from 1984 to 1997. Cotton was planted on conventional tillage and no-tillage plots after winter wheat, hairy vetch, crimson clover, and no winter cover crop alternatives. A burn-down herbicide was used to kill the cover crop before planting cotton in the no-tillage plots. Conventional tillage plots were disked to destroy the cover crop before planting. Winter covers were reestablished each season after cotton harvest. Broadcast ammonium nitrate, the nitrogen source, was applied after planting at rates of 0, 30, 60, and 90 pounds/acre.

Unlike Larson et al., yields from the four replications were not averaged, but instead treated as separate observations and separate production units. Therefore, each of four separate cotton-cover crop systems—no cover, wheat, vetch, and clover covers—has a total of 448 observations available for estimation. The application that follows treats the data as a cross-section and does not take account of the data's panel structure.

In 1995, two important events occurred which complicated the analysis of the yield data. Researchers experienced increasing difficulty with controlling weeds, especially pigweed, and especially in the no-tillage and in the vetch and clover cover crop plots—the two legumes. Starting in 1995, researchers were better able to control pigweed by applying the now available prythiobac sodium (Staple) herbicide. Researchers also applied lime in 1995, at the rate recommended by the Extension Service, after having let pH levels deteriorate through 1994.

Weather and pest data for the noise and inefficiency equations came from several sources. Precipitation during July and August (*Precip*) and growing degree days (*GDD*) were calculated from weather station data recorded at the West Tennessee Experiment Station (U.S. Department of Commerce). Two proxy variables for insect and weed damage, cotton insect damage (*Insects*) and pigweed damage (*Pigweed*), were obtained from statewide average percentage yield damage estimates (Head; Williams; Byrd). Table 1 presents summary statistics on all the experimental data.

Yield Specification

Using these data, the $\mathbf{x}$ vector in the yield equations is specified to include the following: NIT and NIT^2, where NIT equals the pounds per acre of applied ammonium nitrate; $D_{No\text{-}Till}$, a tillage binary variable where no tillage equals 1 and conventional tillage equals 0; $NIT*D_{No\text{-}Till}$, an interaction of NIT and $D_{No\text{-}Till}$; $TIME$, a trend index running from 1984 = 1 to 1997 = 14; D_{1995}, a binary variable equal to one if the experiment year was 1995 or greater; and $NIT*D_{1995}$, an interaction of NIT and D_{1995}.

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[4] While agriculturalists and others may be unaccustomed to inefficiency considerations in experimental data, they may be more familiar with production risk, or noise, in controlled experiments because Just and Pope (1979) applied their model to experimental corn and oats production. Moreover, the use of experimental data for model estimation should alleviate any concerns over inconsistency of results obtained from a production function estimated without also including first-order conditions. (See Love and Buccola, and Shankar and Nelson for a debate of this subject.)

Table 1. Summary Statistics for West Tennessee Cotton Production

Description	Maximum	Minimum	Average	Std. Dev.
Cotton yield with no cover (lbs./acre)	1,275	110	723.0	260.0
Cotton yield following wheat cover (lbs./acre)	1,301	136	757.2	229.7
Cotton yield following vetch cover (lbs./acre)	1,304	103	758.3	260.5
Cotton yield following clover cover (lbs./acre)	1,295	75	743.0	228.0
NIT (applied ammonium nitrate, lbs./acre)	90	0	45	33.6
GDD (growing degree days, cumulative daily temperature above 60°F between May 1 and Oct. 1)	2,803.0	2,162.0	2,480.2	184.6
Precip (cumulative inches of rainfall between July 15 and Aug. 31)	19.9	8.4	12.9	3.7
Insects (estimated annual yield losses to all cotton insects, %)	28.4	0.5	8.2	7.7
Pigweed (estimated annual yield losses to pigweed, %)	15.0	3.0	9.3	4.0

Note: Number of observations = 448 for each cover crop system from 1984–1997 = (14 years) × (4 levels of applied nitrogen) × (2 tillage treatments) × (4 replications).

The variable input, nitrogen, is specified as a quadratic to allow for the possibility of a "stage III" production, where the marginal product is negative, a phenomenon that may be common in cotton systems. Expected signs on these parameters, therefore, are $\beta_{NIT} > 0$, $\beta_{NIT^2} < 0$, though expected results for other parameter estimates are less certain. No-till may, under some circumstances, suppress yields, leading to a negative sign for $\beta_{D_{No\text{-}Till}}$. While technical change is not expected in the controlled experiment, β_{TIME} could be positive if soil quality is improving under certain cover crop or tillage methods, or negative if weed or pest pressures accumulate over the time period. The addition of lime and availability of an alternative herbicide are expected to improve yield, so $\beta_{D_{1995}}$ is expected to be positive. The interaction terms, $NIT*D_{No\text{-}Till}$ and $NIT*D_{1995}$, are included because the tillage method and experimental changes in 1995 could affect the marginal product of nitrogen either positively or negatively.

Risk Specification

The $\mathbf{z}$ (or $\mathbf{z}^v$) vector in the variance or noise equations includes NIT, $D_{No\text{-}Till}$, $NIT*GDD$ (an interaction term between nitrogen and growing degree days), $TIME$, $TIME*D_{No\text{-}Till}$ (an interaction term between time and the no-till dummy), and *Insects*. While substantial empirical literature exists on the risk effects of nitrogen fertilizer for production of various crops (Roumasset et al.; Antle and Crissman; Lambert; Traxler et al.), little information is available about the specific form of the input-output relationship between nitrogen and yield variance. There is no theoretical economic or agronomic reason to suggest nitrogen's marginal risk effect is similar for different crops and cropping systems. Given the lack of knowledge about the nitrogen-variance relationship, nitrogen fertilizer is modeled as a linear function in the variance equation.

Whether or not nitrogen or some other input is risk-increasing or risk-decreasing is an empirical issue, with some studies reporting evidence that nitrogen increases risk (Roumasset et al.), but others finding nitrogen fertilizer reduces risk (e.g., Antle and Crissman; Lambert). In particular, for some crop production systems, nitrogen may decrease noise under ideal weather conditions. Therefore, the interaction term $NIT*GDD$ could be negative if *GDD* reflects increasingly ideal conditions. As indicated previously, no tillage ($D_{No\text{-}Till}$) may positively or negatively affect yield variance depending on weather and pest events that occur during cotton plant growth and development. Because no tillage and winter covers can affect both soil quality and weed pressures over time, the expected sign on the interaction term $TIME*D_{No\text{-}Till}$ is uncertain.

Mean Inefficiency Specification

When the estimated model includes the specification in (5), inputs and other production factors are allowed to influence mean inefficiency by directly affecting the mode of the truncated normal distribution of u_i. As Kumbakhar (2002, p. 10) notes, one may expect technical inefficiency to arise "due to managerial inertia, ignorance, ability, etc." Experimental data, therefore, may not be expected to exhibit inefficiencies except to the extent that managerial inertia or ignorance was intentionally or unintentionally built into the experimental design. More specifically, managerial inertia could correspond to input usage and other management variables which were determined during the experimental design stage, and therefore not adjusted over the experiment's duration. Intentional or unintentional ignorance could occur due to the failure to account for year-to-year variation in the growing environment or skillfulness of experimental labor.

Given the definite possibility of inefficiencies, the $\mathbf{z}^u$ vector in (5) was specified to include factors which may reflect managerial inertia or ignorance.[5] More specifically, $\mathbf{z}^u$ included nitrogen applied in the previous year, $NIT(-1)$, as well as $D_{No\text{-}Till}$, *GDD*, *Precip*, and *Pigweed*.

Results

Tables 2a, b, c, and d present results from the maximum-likelihood estimation of (1) and (2), (1) and (3), (1) and (4), and (1) and (5), respectively. Convergence of the maximum-likelihood estimator proved difficult for the stochastic frontier models with heteroskedasticity in the noise term and/or heterogeneity in the mean inefficiency term, as it appears the likelihood function is not well-behaved. Nonetheless, convergence was obtained by adjusting starting values or step-size criteria.

Results for the Just-Pope and stochastic frontier models are, for the most part, more similar than different. In general, the estimated coefficients for the yield equations are of the expected signs and significant. Exceptions include the estimates for *NIT* and NIT^2 coefficients for the three cover-crop systems. For all three cover-crop systems—wheat, vetch, and clover—the signs of these estimates are opposite the expected sign for some of the stochastic frontier models; and for the two legume cover-crop systems of vetch and clover, the significance of these estimates is low for many models, including the Just-Pope model. In retrospect, it is not surprising to find that the expected nitrogen response may be confounded with nitrogen-fixing legume cover crops since the cotton crop has two potential sources for available nitrogen: nitrogen applied as fertilizer and nitrogen fixed

[5] One recurring issue in the efficiency literature involves the choice of what factors to include in the frontier, or yield, equation and what to include in the mean inefficiency equation (see, e.g., Kumbhakar and Lovell for more discussion). A second issue is the use of a one-step or two-step estimation procedure. Wang and Schmidt, for example, strongly advocate a one-step procedure, which this paper employs.

Table 2a. Maximum-Likelihood Estimation: Cotton with No Cover Crop

Description	Just-Pope	Stochastic Frontier	Stochastic Frontier Heteroskedasticity in v	Stochastic Frontier Heteroskedasticity in v, Heterogeneity in μ
Yield Equation:				
Constant	6.961***	7.230***	7.161***	7.089***
	(154.2)	(145.0)	(53.09)	(87.17)
NIT	0.175***	0.149***	0.154**	0.174***
	(3.831)	(3.877)	(2.018)	(2.622)
NIT^2	-0.049***	-0.038***	-0.028	-0.031*
	(-3.513)	(-3.340)	(-1.433)	(-1.871)
$NIT*D_{1995}$	0.101***	0.065*	0.144**	0.027
	(2.949)	(1.709)	(2.292)	(1.000)
$NIT*D_{No\text{-}Till}$	0.038	0.048**	-0.094**	0.082***
	(1.509)	(2.461)	(-2.543)	(2.765)
$D_{No\text{-}Till}$	-0.197***	-0.206***	0.217**	-0.119**
	(-4.173)	(-5.096)	(2.027)	(-2.289)
D_{1995}	0.589***	0.327***	0.136**	0.284***
	(8.039)	(5.364)	(2.070)	(5.618)
TIME	-0.086***	-0.059***	-0.052***	-0.052***
	(-17.710)	(-13.091)	(-4.879)	(-11.250)
Noise Equation:				
σ_v (constant term)	0.268***	0.091	0.372	0.637***
	(8.467)		(1.001)	(2.815)
NIT	0.706		0.102	0.246
	(1.296)		(0.026)	(0.094)
$D_{No\text{-}Till}$	0.172		0.287	0.496
	(0.609)		(0.643)	(0.501)
$NIT*GDD$	-0.287		-0.423	-0.501
	(-1.315)		(-0.256)	(-0.436)
Insects	-0.027***		0.011	-0.164***
	(-2.774)		(0.454)	(-4.978)
$TIME*D_{No\text{-}Till}$	0.005		-0.178	-0.398
	(0.154)		(-1.088)	(-1.447)
TIME	0.049***		-0.207***	-0.072***
	(2.085)		(-5.807)	(-2.805)
σ_u		0.502	0.364***	0.298***
			(9.627)	(77.473)
Mean Inefficiency Equation:				
Constant				-0.825
				(-0.162)
$NIT(-1)$				0.364
				(1.442)
$D_{No\text{-}Till}$				-0.083
				(-0.140)
GDD				1.098
				(0.660)
Precip				-0.094
				(-0.988)
Pigweed				-0.470***
				(-6.569)
λ		5.517***		
		(4.739)		
σ		0.510***		
		(25.068)		

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are t-statistics. A Breusch-Pagan test and a Wald test imply the presence of heteroskedasticity in the Just-Pope model.

Table 2b. Maximum-Likelihood Estimation: Cotton with a Wheat Cover Crop

Description	Just-Pope	Stochastic Frontier	Stochastic Frontier Heteroskedasticity in v	Stochastic Frontier Heteroskedasticity in v, Heterogeneity in μ
Yield Equation:				
Constant	6.959***	7.134***	7.451***	7.092***
	(198.8)	(155.3)	(70.962)	(107.98)
NIT	0.143***	0.184***	-0.306***	0.280***
	(3.929)	(5.252)	(-3.370)	(5.386)
NIT^2	-0.038***	-0.048***	0.090***	-0.063***
	(-3.387)	(-4.778)	(4.121)	(-3.820)
$NIT*D_{1995}$	0.112***	0.062**	0.139***	-0.059*
	(3.844)	(2.035)	(3.322)	(-1.730)
$NIT*D_{No\text{-}Till}$	0.070***	0.058***	0.092**	0.079***
	(3.495)	(3.261)	(2.214)	(5.267)
$D_{No\text{-}Till}$	-0.202***	-0.174***	-0.135	-0.276***
	(-5.361)	(-5.128)	(-1.582)	(-8.530)
D_{1995}	0.363***	0.255***	0.227***	0.500***
	(5.861)	(5.777)	(2.925)	(5.074)
TIME	-0.070***	-0.052***	-0.061***	-0.053***
	(-18.088)	(-12.202)	(-11.478)	(-7.619)
Noise Equation:				
σ_v (constant term)	0.165***	0.084	-1.312***	-0.157
	(8.467)		(-4.159)	(-1.364)
NIT	0.371		1.432	0.286
	(0.681)		(1.070)	(0.192)
$D_{No\text{-}Till}$	0.445		-0.272	0.094
	(1.577)		(-0.414)	(0.452)
*NIT*GDD*	-0.152		-0.760	-0.592
	(-0.694)		(-1.335)	(-0.970)
Insects	0.002		0.004	-0.168***
	(0.240)		(0.362)	(-8.855)
$TIME*D_{No\text{-}Till}$	-0.056*		-0.055	-0.094***
	(-1.679)		(-0.796)	(-4.666)
TIME	0.099***		0.026	0.126***
	(4.191)		(0.936)	(9.600)
σ_u		0.384	0.774***	0.384***
			(18.014)	(72.577)
Mean Inefficiency Equation:				
Constant				0.209
				(0.028)
NIT(−1)				0.241
				(0.441)
$D_{No\text{-}Till}$				0.003
				(0.004)
GDD				0.104
				(0.043)
Precip				-0.271
				(-1.402)
Pigweed				-0.155
				(-1.120)
λ		4.572***		
		(4.529)		
σ		0.393***		
		(30.598)		

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are *t*-statistics. A Wald test, but *not* a Breusch-Pagan test, implies the presence of heteroskedasticity in the Just-Pope model.

Table 2c. Maximum-Likelihood Estimation: Cotton with a Vetch Cover Crop

Description	Just-Pope	Stochastic Frontier	Stochastic Frontier Heteroskedasticity in v	Stochastic Frontier Heteroskedasticity in v, Heterogeneity in μ
Yield Equation:				
Constant	7.100***	7.421***	7.581***	7.410***
	(165.9)	(165.4)	(61.798)	(45.15)
NIT	0.037	0.015	-0.228**	0.199***
	(0.916)	(0.548)	(-2.525)	(3.400)
NIT^2	-0.024*	-0.019**	0.031	-0.088***
	(-1.840)	(-1.981)	(1.321)	(-6.159)
$NIT*D_{1995}$	0.081***	0.059*	0.164*	0.060
	(3.055)	(1.937)	(1.864)	(1.579)
$NIT*D_{No\text{-}Till}$	-0.071***	-0.009	-0.044	0.045
	(-2.821)	(-0.461)	(-1.241)	(1.428)
$D_{No\text{-}Till}$	-0.065	-0.064	0.074	-0.228***
	(-1.589)	(-1.449)	(0.762)	(-2.678)
D_{1995}	0.488***	0.337***	-0.125	0.263***
	(9.201)	(5.583)	(-0.900)	(3.159)
TIME	-0.070***	-0.060***	-0.034***	-0.052***
	(-14.289)	(-13.485)	(-3.351)	(-3.584)
Noise Equation:				
σ_v (constant term)	0.220***	0.041	0.478	0.195
	(8.467)		(0.458)	(0.502)
NIT	1.659***		1.054	0.045
	(3.043)		(0.265)	(0.029)
$D_{No\text{-}Till}$	1.017***		0.067	0.042
	(3.605)		(0.082)	(0.097)
$NIT*GDD$	-0.568***		-0.731	-0.107
	(-2.600)		(-0.477)	(-0.176)
Insects	0.036***		-0.108	-0.056*
	(3.764)		(-1.070)	(-1.884)
$TIME*D_{No\text{-}Till}$	-0.033		-0.102	-0.057
	(-1.004)		(-0.423)	(-0.721)
TIME	-0.058**		-0.198	-0.170***
	(-2.450)		(-1.099)	(-2.697)
σ_u		0.550	0.408***	0.041***
			(9.733)	(3.119)
Mean Inefficiency Equation:				
Constant				-0.079
				(-0.028)
$NIT(-1)$				0.091
				(0.459)
$D_{No\text{-}Till}$				0.031
				(0.075)
GDD				0.109
				(0.100)
Precip				0.003
				(0.065)
Pigweed				-0.155***
				(-2.803)
λ		13.350***		
		(2.842)		
σ		0.552***		
		(33.358)		

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are t-statistics. A Breusch-Pagan test and a Wald test imply the presence of heteroskedasticity in the Just-Pope model.

Table 2d. Maximum-Likelihood Estimation: Cotton with a Clover Cover Crop

Description	Just-Pope	Stochastic Frontier	Stochastic Frontier Heteroskedasticity in v	Stochastic Frontier Heteroskedasticity in v, Heterogeneity in μ
Yield Equation:				
Constant	7.041***	7.266***	7.582***	7.280***
	(204.8)	(238.3)	(78.198)	(44.87)
NIT	0.021	-0.037	-0.438***	0.070
	(0.559)	(-1.109)	(-5.438)	(0.894)
NIT^2	-0.011	0.008	0.104***	-0.057***
	(-0.959)	(0.781)	(5.545)	(-3.415)
$NIT*D_{1995}$	0.057*	0.014	0.242***	0.007
	(1.799)	(0.501)	(5.151)	(0.181)
$NIT*D_{No\text{-}Till}$	0.010	0.005	0.089**	0.162***
	(0.447)	(0.285)	(2.069)	(3.362)
$D_{No\text{-}Till}$	-0.061	-0.018	-0.109	-0.487***
	(-1.502)	(-0.522)	(-1.340)	(-4.052)
D_{1995}	0.444***	0.418***	0.114	0.223***
	(6.839)	(9.286)	(1.576)	(2.889)
TIME	-0.070***	-0.056***	-0.051***	-0.025**
	(-16.244)	(-16.672)	(-9.027)	(-2.140)
Noise Equation:				
σ_v (constant term)	0.118***	0.069	0.100	0.095
	(8.467)		(0.225)	(0.504)
NIT	1.054*		1.584	-0.093
	(1.932)		(0.794)	(-0.128)
$D_{No\text{-}Till}$	1.548***		0.217	0.027
	(5.486)		(0.505)	(0.131)
$NIT*GDD$	-0.391*		-0.810	-0.062
	(-1.790)		(-1.036)	(-0.212)
Insects	0.049***		-0.082**	-0.065***
	(5.033)		(-2.201)	(-4.597)
$TIME*D_{No\text{-}Till}$	-0.166***		-0.005	-0.048
	(-5.022)		(-0.066)	(-1.226)
TIME	0.136***		-0.151**	-0.086***
	(5.745)		(-2.001)	(-2.848)
σ_u		0.463	0.526***	0.138***
			(13.129)	(13.565)
Mean Inefficiency Equation:				
Constant				0.273
				(0.071)
$NIT(-1)$				-0.036
				(-0.108)
$D_{No\text{-}Till}$				0.254
				(0.385)
GDD				-0.198
				(-0.130)
Precip				-0.171*
				(-1.700)
Pigweed				-0.002
				(-0.019)
λ		6.684***		
		(5.374)		
σ		0.468***		
		(38.298)		

Notes: Single, double, and triple asterisks (*) denote significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses are t-statistics. A Breusch-Pagan test and a Wald test imply the presence of heteroskedasticity in the Just-Pope model.

by the legume cover crop. The estimates on *TIME* in the yield equation are all negative and significant, possibly indicating that increasing weed and pest pressures may more than offset any improvements in soil quality over time.

For all four model specifications and all four cover-crop systems, very few estimates of the noise equation coefficients differ significantly from zero (table 2). Both the coefficients' sign and significance level differ widely across models and across cover-crop systems. For the no cover and wheat systems, there is no evidence from any of the four models to suggest nitrogen is a risk-increasing input. This result differs from the findings of Larson et al., in which (using weighted least squares) nitrogen was found to be risk-increasing in the presence of a wheat cover. As shown from table 2, for both the vetch and clover cover-crop systems, the Just-Pope model finds nitrogen is risk-increasing. Larson et al. note a similar result for the vetch cover-crop system, but not the clover system. However, table 2 also shows that the stochastic frontier models with heteroskedasticity in the noise term and heterogeneity in the mean inefficiency term fail to find evidence of nitrogen's risk-increasing effect in the vetch and clover systems.

Estimates of the time-trend variable (*TIME*) are often found to differ significantly from zero, but the sign of the estimates varies across model specification and cover-crop system. For most cover-crop systems, table 2 reports that time's passage decreases the cropping system's noise (i.e., the estimate is negative). However, this term is positive (risk-increasing) for the no cover system estimated with the Just-Pope model, for the wheat system using all models, and for the clover system using the Just-Pope model. Additionally, the sign and significance of the estimate for the insect damage proxy variable varies across cropping system and model specification. Finally, estimation with a Just-Pope model shows no tillage ($D_{No\text{-}Till}$) increases risk for vetch and clover, the two legume cover crops. Estimates of these coefficients using the stochastic frontier models with heteroskedasticity in the noise term and/or heterogeneity in the mean inefficiency term fail to find any significant marginal risk effects for no tillage.

Table 2 also presents results from marginal effects of inputs on mean inefficiency (in the stochastic frontier model with heteroskedasticity in the noise term and heterogeneity in the mean inefficiency term). These results reveal that very few (almost none) of the δ^u coefficients are found to differ significantly from zero. An exception is the weed damage proxy coefficient (*Pigweed*) for the no cover and vetch cover-crop systems, which is found to be negative and significant—thereby decreasing inefficiency. Also, for the clover cover-crop system, precipitation is positive and significant, increasing inefficiency for the clover system.

When facing the decision of which results among the four models to trust, recall the Just-Pope model specification is a special case of specifications for the stochastic frontier models with heteroskedasticity in the noise term and/or heterogeneity in the mean inefficiency term. A Wald test of the most general model, (1) and (5), imposing restrictions that $\delta^v = 0$, $\delta^u = 0$, and $\sigma_u^2 = 0$, fails to reject the null, thereby implying heteroskedasticity in the noise term and heterogeneity in the mean inefficiency term are appropriate.

An important discrepancy between the Just-Pope and stochastic frontier results is found in the rankings of the estimated residual variances. Table 3 shows the variance estimates for the noise residuals (σ_v^2) for the Just-Pope and stochastic frontier models. For both models, the no cover system is found to be the riskiest. Using the Just-Pope specification, the vetch system is found to be the second riskiest, and the clover system to be the least risky. However, estimation with the stochastic frontier model dramatically reorders vetch's ranking: the vetch system is now observed to be the least risky.

Table 3. Estimates of Residual Component Variances

Just-Pope, σ_v^2		Stochastic Frontier, σ_v^2		Stochastic Frontier, σ_u^2	
No Cover	0.072	No Cover	0.0083	Vetch	0.3030
Vetch	0.049**	Wheat	0.0071**	No Cover	0.2517**
Wheat	0.027**	Clover	0.0048**	Clover	0.2144**
Clover	0.014**	Vetch	0.0017**	Wheat	0.1477**

Notes: Double asterisks (**) denote statistically different from the above variance estimate at the 5% level, based on an F-test. For example, in the bottom row of the first column, the variance associated with the clover cover crop (0.014) is compared to the variance above it (0.027 for the wheat cover crop) and found to be statistically different.

The relative riskiness of the cotton-cover crop systems, and the reordering in the two estimation frameworks, can be seen graphically in figure 1, which illustrates the estimated distribution of noise component residuals. Figure 2 generally shows that the same relative order of residuals' dispersion can also be seen in the distribution of $\varepsilon = v - u$, recovered in the stochastic frontier model.

Figure 3 (panels a, b, c, and d), which graphically presents estimates of technical efficiency, $TE = \exp(-u)$, attempts to shed light on the extent of inefficiency in each of the four cotton-cover crop systems. In each system, the *TE* estimate for each cotton plot is ranked from lowest (most inefficient) to highest (most efficient). Confidence intervals for *TE* according to Horrace and Schmidt are presented graphically along with *TE* estimates and the overall mean. As observed from the four graphs in figure 3, the ranked *TE* estimates for each of the cotton-cover crop systems are remarkably similar. The wheat system has the highest average efficiency ($TE = 0.765$ averaging all plots), followed by clover (0.727), no cover (0.701), and finally vetch (0.687). However, the vetch system appears to have the tightest confidence intervals in each estimate.

Examination of table 3, and to some degree figure 3, makes clear that much of the perceived noise in the cotton-cover crop systems, when estimated with the Just-Pope specification, shows up in the inefficiency component when estimated with the stochastic frontier specification. This result holds even for the cotton-vetch system, which has the tightest confidence intervals. Specifically, while vetch ranks as the least risky in the stochastic frontier model, it has the highest inefficiency residual variance, σ_u^2. From a practitioner's perspective, however, the extent of inefficiency, the implications of this result, and its remedy may as yet remain unclear.

Conclusions and Implications

This study has investigated whether input use has a mutual effect on both production risk and technical inefficiency. To the extent that inefficiencies tend to obscure the assessment of inputs' marginal risk effects, one must take steps to disentangle these two portions of the estimated residuals. Rather than use a typical Just-Pope framework, we also employ a stochastic frontier framework, which accounts for both noise and inefficiency, to conduct our risk analysis. Moreover, we have estimated these mutual effects simultaneously using maximum-likelihood techniques in what is among the first empirical applications of this type. Disentangling the mutual effect therefore proves not only feasible, but also important for empirical reasons, at least when investigating west Tennessee cotton-cover crop production systems.

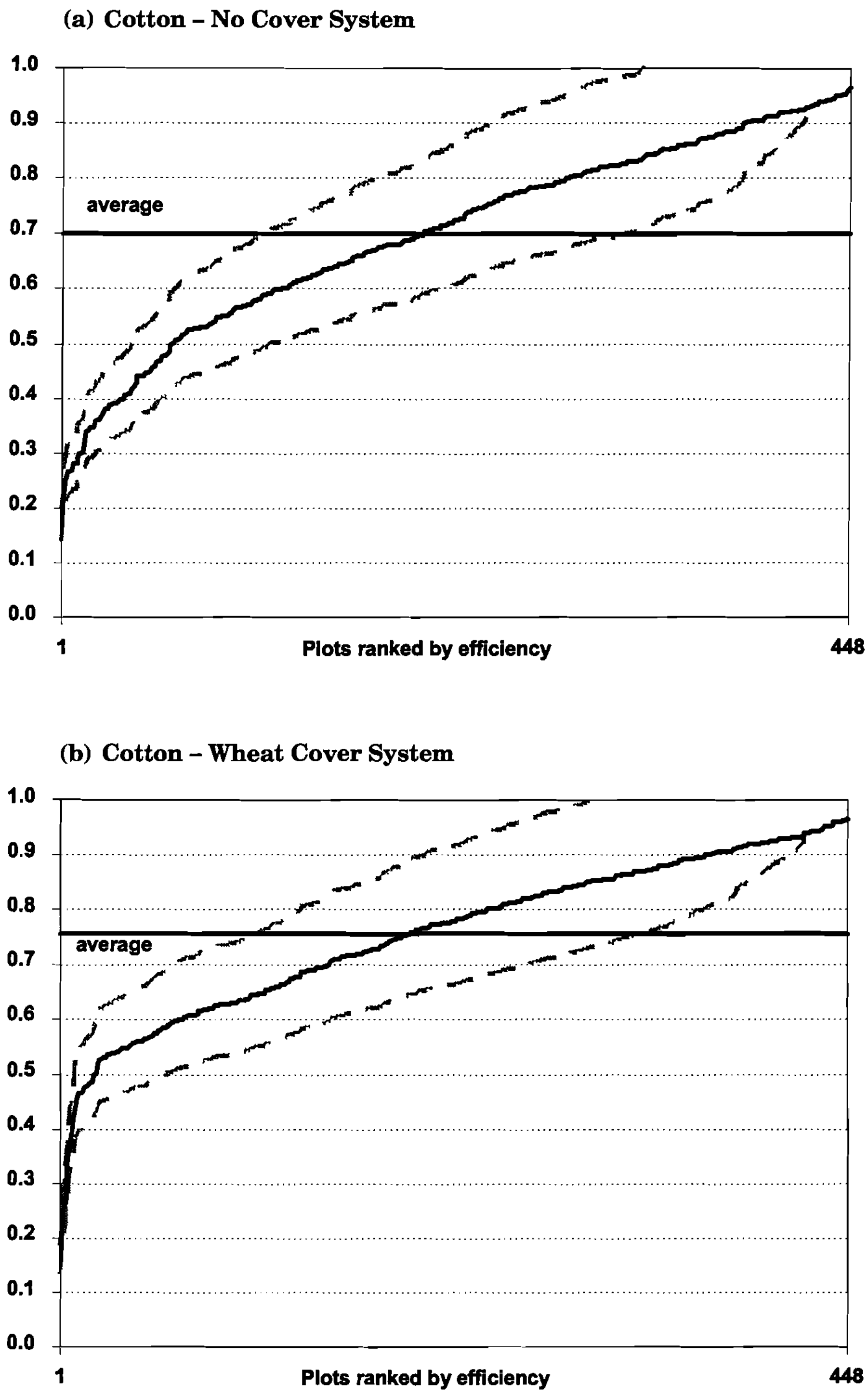
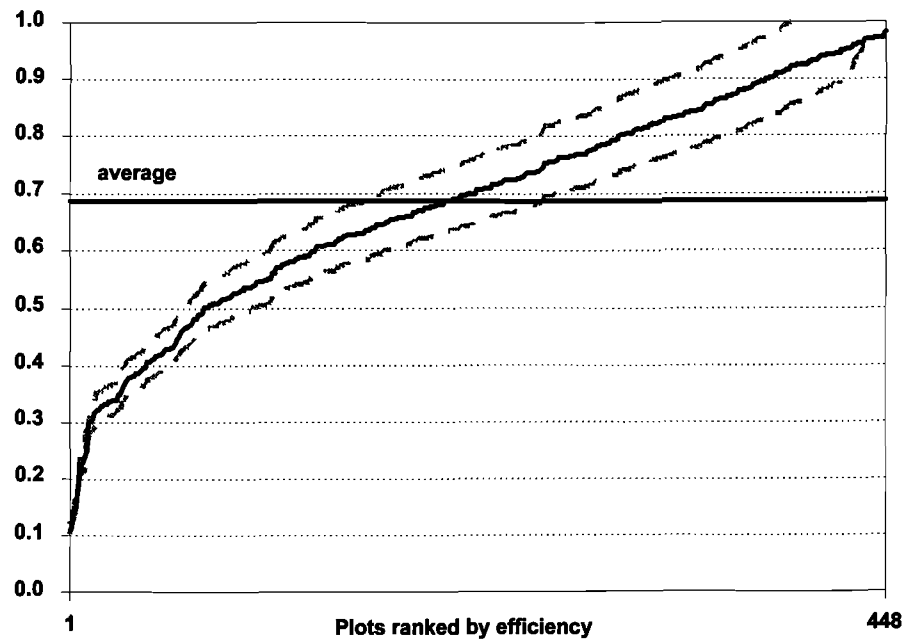


Figure 3. Technical efficiency and confidence intervals, Stochastic Frontier model

(c) Cotton – Vetch Cover System



(d) Cotton – Clover Cover System

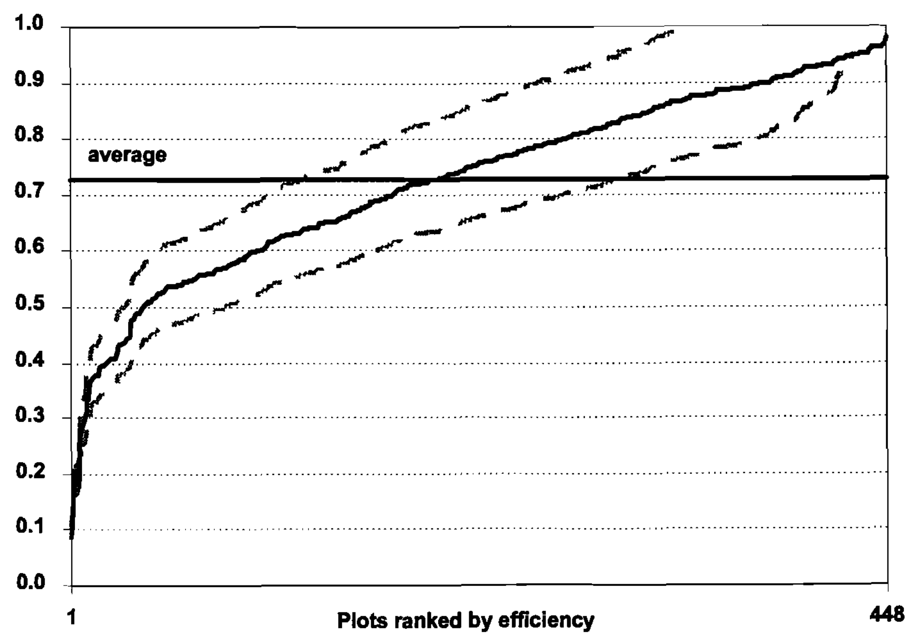


Figure 3. (Continued)

The primary implication of the models estimated is that the stochastic frontier models, with their composed error term containing both a two-sided noise component and a one-sided inefficiency component, alter the observed risk effects of the cotton-cover crop systems. Perhaps most striking is the fact that the frontier model reorders the relative riskiness of cover-crop regimes associated with cotton systems. For example, one of the legume cover crops (vetch) is shown to generate the least amount of production risk, as compared with other cover crops or no cover, only when technical inefficiency is accounted for using the stochastic frontier model. Without accounting for the mutuality in the input effects, the vetch system would instead appear to be the second riskiest, after cotton grown with no cover. Results from the more general frontier models provide less support than the Just-Pope model for empirically characterizing nitrogen as a risk-increasing input in these cotton-cover crop systems. Specifically, nitrogen would have been found to be risk-increasing when cotton is grown with vetch and clover cover crops using the Just-Pope model, but the more general stochastic frontier models fail to show this effect.

The corollary to the primary implication is that researchers and agricultural practitioners may need to confront observed inefficiencies as well as risk, even in experimental production. Based on the estimation results for all cotton-cover crop systems, the variance of the inefficiency component was at least as important as the noise component. While this result may surprise researchers familiar with experimental data, the reasons for observed inefficiencies may well be the same as for those encountered with firm-level behavioral data, namely inertia and ignorance. Our research suggests that inefficiencies, apart from production risk, are a substantial component of cotton-cover crop systems. However, we fail to document a precise relationship between the production inputs and inefficiency. This result points to the need for more empirical investigations of not just the relative riskiness of cover crops, but also the relative inefficiency of cover crop practices.

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